

Inflation Dynamics and Their Impact on Global Financial Markets: A Time Series Approach to Risk Modeling

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Abstract:

This paper examines the dynamics of inflation and the impact of inflation uncertainty on various asset classes. The results are somewhat surprising. Although inflation uncertainty had the most significant impact on commodities during normal times, this relationship reverses as inflation uncertainty sets in, with commodities underperforming and portfolio managers returning to the 10-Year Treasury as a safe asset. In addition, an equally weighted portfolio yielded higher returns during stress periods than normal periods, though volatility also increased. These findings suggest that inflation hedges depend on the regime and that portfolios can achieve higher returns in stress periods if properly managed. Motivated by the 2021-2023 inflation surge, during which markets were repeatedly caught off guard by unanticipated CPI increases, this paper addresses the effectiveness of ARIMA modeling in measuring inflation surprises, the ability of GARCH to model inflation uncertainty, and the extent these variables explain return dynamics across equity, fixed income, commodity, and currency markets. Using monthly U.S. data from 2000-2024, this paper applies a two-stage ARIMA-GARCH analysis to isolate unexpected inflation and estimate uncertainty, then examines effects across major asset classes and constructs an equal-weighted portfolio.

Keywords: Inflation uncertainty; Inflation surprises; ARIMA-GARCH; Cross-asset returns; Portfolio risk management.

1. Introduction

This paper is motivated by the 2021–2023 inflation surge. The most acute in four decades, this spike was driven by large-scale COVID-19 fiscal stimulus

and supply chain disruptions, resulting in inflation reaching a peak in June 2022, when the CPI peaked at 9.1%. It is important to note that while moderate inflation, when anticipated, is an inherent characteristic of economic activity, unanticipated inflation can

have significant consequences for financial markets. The COVID surge provides a compelling context for this paper because policymakers initially dismissed rising prices as transitory, thereby showcasing the surprise component when CPI repeatedly failed to return to the baseline [1]. Inflation deviations from what the market has anticipated force rapid reassessments of asset valuations and risk premiums, fundamentally altering expectations for monetary policy across global markets. When inflation spiked in 2021, the Fed began rapidly increasing rates; global equity markets entered a bear market; and demand for the U.S. dollar surged as the Fed's actions resulted in significant capital inflows [2].

The impact of unexpected inflation on the financial market differs based on the specific markets. CPI surprises are generally associated with lower stock prices since unexpected inflation increases the discount rate. If the inflation shock occurs and is domestic, it may weaken both the domestic currency and fixed income markets since inflation erodes the real value of each coupon payment as well as the currency's purchasing power. It can also change market's monetary policy expectations. Unlike the previous three asset classes, precious commodities such as gold can actually appreciate during periods of inflation surprises, making them hedges against inflation [3].

This paper addresses three research questions: the reliability of ARIMA derived inflation surprises; the accuracy of GARCH derived inflation uncertainty, and their combined explanatory power for cross asset returns. The main purpose of this paper is to conduct cross-market regressions using inflation-related variables and predict stress period returns for a simulated portfolio. To achieve this, this paper measures inflation surprises through ARIMA residuals and models the resulting volatility clustering with GARCH to capture time-varying inflation uncertainty [4, 5].

2. Literature Review

The distinction between expected and unexpected inflation is essential for understanding how macroeconomic news moves financial markets. Under rational expectations, only the surprise component of a CPI release should generate abnormal returns because anticipated inflation is already baked into asset prices. Gürkaynak, Sack, and Swanson formalized this in an event-study framework, showing that financial markets respond sharply and immediately to the unanticipated component of inflation while eliciting no response towards pre-announced changes [6]. During the 2021–2023 inflation surge, different aspects of the market, including bond yields, market-implied inflation expectations, and other assets, reacted sharply to CPI releases [7]. It becomes clear that accurately measuring the unexpected component of inflation — as this paper does via ARIMA

residuals — is foundational to identifying its cross-asset effects.

When it comes to the equity market, real-world data consistently shows an inverse relationship between inflation surprises and its returns. Investors tend to hold a stagflationary view of inflation surprises: unexpected CPI increases leave nominal cash flows stagnant while simultaneously increasing discount rates, thereby resulting in lower stock prices through both channels [8]. Chiang substantiates this view, stating that inflation increases equity market volatility, exerting an additional negative drag on stock returns [9]. This finding remains robust across 12 developed economies and suggests that inflation surprises affect both a levels channel (lower expected profits) and a volatility channel (higher uncertainty), implying the need for a two stage ARIMA-GARCH system to fully separate the mechanisms.

The currency market response to inflation surprises operates primarily through a conditional monetary policy expectations channel. Clarida and Waldman demonstrate that a surprise inflation surge appreciates the domestic currency when the market expects the central bank to target inflation through its policy [10]. For the U.S. dollar specifically, this implies that the DXY response to CPI surprises is conditioned on whether the market anticipates the Federal Reserve raising rates. If markets do expect rates to increase, capital will flow into the U.S., pushing the dollar up. However, if markets believe the Fed will be unresponsive, then inflation is simply eroding the dollar's purchasing power, and the dollar weakens as a result.

Bond markets are the most directly exposed asset class to inflation surprises because price changes directly decrease the real value of fixed coupon payments. This decrease prompts upward revisions to expected future policy rates, which increases yields sensitivity drastically. Bauer, Pflueger, and Sunderam document this mechanism using regressions of two-year Treasury yield changes on core CPI surprises, finding that yield sensitivity rose sharply after the Federal Reserve began tightening in 2022, with both positive and negative surprises producing large symmetric yield adjustments [11].

While commodities are typically seen as hedges in periods of intense inflation surprises, the effectiveness of commodity futures indices is being challenged by recent studies. Gorton and Rouwenhorst found that broad commodity futures indices can deliver equity-like returns and meaningful inflation-hedging benefits over long horizons [12]. However, a recent study done by Liu, Zhang, and Zhou claimed that total commodity futures as a broad index fail to hedge inflation consistently [13]. Despite the debate around commodity indices, certain physical commodities are more commonly accepted to have strong effect in adverse environments. Energy commodities, particularly crude oil and gasoline, demonstrate the strongest

inflation-hedging properties, with hedging effectiveness varying across macroeconomic backdrops [14]. Since this paper uses the PPI All Commodities index, these findings suggest that aggregate commodity returns will exhibit a positive but unstable response to inflation surprises, with volatility clustering during periods of supply-driven price shocks.

Inflationary periods can alter cross-asset correlations in ways that undermine typical portfolio diversification. In fact, high-inflation regimes systematically invert stock-bond correlations from their usual negative to positive [15]. During the inflationary periods of 2021, the correlation turned positive, and remained above 0.5 through 2024, as both asset classes simultaneously declined, disproving the traditional belief that had defined portfolio construction for the prior two decades [16].

3. Data

This study employs five monthly time series spanning January 2000 to December 2024, a 25-year window that encompasses multiple inflationary regimes — the post-dot-com disinflation, the Global Financial Crisis, the decade-long low-inflation expansion of the 2010s, and the post-pandemic inflation surge of 2021–2023. Together, these episodes provide meaningful variation for identifying the relationship between inflation uncertainty and cross-asset return dynamics.

Inflation. The primary series is the U.S. Consumer Price Index (Not Seasonally Adjusted, All Urban Consumers) sourced from the Bureau of Labor Statistics, computed as the log difference of the index level. The NSA measure is preferred because seasonal adjustment distorts the high-frequency volatility structure that GARCH models are designed to capture.

Equities. Equity market performance is measured by the monthly total return on the S&P 500 index, measured in log differences of the price index. This represents the U.S. large-cap equity market.

Fixed income. Bond market exposure is captured through monthly changes in the 10-year U.S. Treasury yield, expressed in first differences of yield levels (in percentage points) rather than log differences, the standard practice for interest rate series. Because bond prices move inversely with yields, a positive yield change corresponds to a capital loss on long positions.

Currency. The U.S. Dollar Index (DXY) — a trade-weighted basket of six major currencies — proxies for dollar strength and broad currency market conditions. Monthly returns are computed as log differences of the index level.

Commodities. PPI All Commodities index (PPIACO), taken as log differences, represents the commodity asset class. PPIACO is a measure of selling prices received by

US producers spanning energy, metals, and agricultural contracts.

Stationarity and transformations. All log-difference return series are expected to be stationary by construction, but this is formally confirmed using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The two tests are applied jointly because they test opposing null hypotheses; a series is deemed stationary when it rejects ADF and fails to reject KPSS. The 10-year Treasury yield change series is also tested in first-differenced form prior to inclusion.

4. Methodology

This study uses a sequential framework to first isolate the surprise component of inflation, determine inflation uncertainty, and then trace its effects across different asset markets. The entire process contains four stages: ARIMA modeling to extract inflation surprises, GARCH modeling to quantify inflation uncertainty, cross-market regression analysis, and a historical stress testing framework applied to a simulated portfolio.

4.1 ARIMA Modeling of Inflation Dynamics

ARIMA modeling constructs a monthly inflation surprise series from the Consumer Price Index (CPI). CPI stationarity is confirmed using the ADF and KPSS tests described in Section 3.

ARIMA model order is selected using the `auto.arima()` function in R, which searches across different (p,d,q) combinations and chooses the combination that minimizes the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). After ARIMA model has chosen the combination, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the differenced series are used as a diagnostic check to ensure the validity of the selection. The chosen ARIMA (p,d,q) model is then estimated on the full sample, capturing the systematic, predictable component of inflation.

Model adequacy is evaluated through standard diagnostics. The Ljung-Box Q-statistic is applied to the residuals to test for remaining serial autocorrelation. The ideal result would be a failure to reject the null of no autocorrelation, which indicates that the ARIMA specification has successfully absorbed the predictable structure in inflation. In addition to the Ljung-Box statistic, residual plots and the Jarque-Bera test are used to assess distributional properties.

The residuals from the fitted ARIMA model, referring to the portion of inflation that was not anticipated by the model's information set, constitute the inflation surprise series, following Fama and Gibbons, who demonstrated that ARIMA residuals provide a theoretically grounded and empirically tractable proxy for unexpected infla-

tion [4]. These residuals are then used in the subsequent GARCH modeling that determines inflation uncertainty across different months.

4.2 GARCH Modeling of Inflation Uncertainty

A second-stage GARCH(1,1) model is applied to the surprise series because ARIMA residuals on their own do not directly measure the time varying degree of uncertainty [17].

Prior to estimation, the presence of ARCH effects in the residual series is confirmed using Engle's Lagrange Multiplier test, which evaluates whether squared residuals exhibit autocorrelation — a necessary condition for GARCH modeling [5]. The GARCH(1,1) specification models the conditional variance at time t (as Equation (1):

(1)

where ϵ_t^2 is the lagged squared shock and σ_t^2 is the lagged conditional variance. The parameters ω and α_1 capture the immediate impact of new information and the persistence of volatility, respectively. The fitted conditional variance series serves as a time-varying proxy for inflation risk, rising during periods of elevated uncertainty — such as the 2021–2023 inflation surge — and declining as price dynamics stabilize.

4.3 Cross-Market Impact Analysis

The third stage examines how inflation uncertainty affects different asset classes. Prior to estimation, the correlation between the ARIMA surprise series and the GARCH conditional variance is assessed to evaluate potential multicollinearity. If correlation is sufficiently low, both variables are included as separate regressors. For each of the four markets — equities (S&P 500), fixed income (10-year Treasury yield), currency (DXY), and commodities (PPI All Commodities Index) — the following regression is estimated (Equation 2):

(2)

where $r_{i,t}$ is the monthly return of asset i , s_t is the ARIMA-derived inflation surprise, and σ_t^2 is the GARCH conditional variance. The coefficient β_1 captures the directional sensitivity of each asset to unexpected inflation, and the coefficient β_2 measures the sensitivity of that asset to conditional inflation uncertainty. If correlation is high, an interaction term is used instead (Equation 3):

(3)

where β_3 captures the sensitivity of each asset to inflation surprises that occur under elevated uncertainty.

4.4 Stress Testing Framework

Although the monthly return of each asset has now been

predicted using inflation-related variables, these statistical findings need to be translated into a portfolio risk context. Historical stress episodes are identified as months in which the GARCH conditional variance exceeds a threshold of 1.5 standard deviations above its mean, corresponding to periods of elevated inflation uncertainty. Inside this method, three such episodes are selected within the sample period to represent distinct inflationary periods.

A portfolio comprising the four asset classes is simulated across each stress episode, and its returns are computed as the simple average of the four asset returns due to the equal weighted character of the portfolio. Peak-to-trough drawdown is estimated for each scenario. The GARCH conditional variance estimates from Section 4.2 are incorporated to scale the uncertainty of each drawdown estimate, providing a volatility-adjusted measure of portfolio vulnerability. Comparing drawdown magnitudes across the three stress episodes as well as with calm periods allows an assessment of whether higher inflation surprise intensity, as measured by the ARIMA-GARCH system, systematically corresponds to greater portfolio loss. It also addresses whether asset-class diversification provides meaningful protection during inflationary stress periods.

5. Results and Discussion

5.1 ARIMA Findings: Inflation Dynamics and Surprise Extraction

Stationarity of the monthly CPI log-difference series was confirmed using the ADF and KPSS tests. According to the table, the ADF test rejected the unit root null, while the KPSS statistic failed to reject level stationarity (Table 1). No differencing was required.

Model selection identified an ARIMA(0,0,2)(2,0,0) specification, with the MA(2) component capturing short-run inflation persistence over a two-month horizon, and the SAR(2) component reflecting systematic seasonal price cycles in energy, food, and shelter costs (Table 2) [12]. The model mean of 0.0021 corresponds to an average monthly inflation rate of 0.21%, consistent with the Federal Reserve's long-run 2% annual target (Table 2).

The Ljung-Box test failed to reject the null of no serial correlation at the 5% level, indicating that no meaningful autocorrelation structure remains in the residuals (Table 3). The extracted inflation surprise series has a mean of effectively zero and symmetric dispersion, confirming it captures genuinely unanticipated inflation deviations (Fig. 1). This surprise series serves as an important regressor in the subsequent GARCH and cross-asset analyses.

Table 1. Stationarity Tests on Monthly CPI Log-Differences

Test	Statistic	p-value	Null Hypothesis	Conclusion
Augmented Dickey-Fuller	-6.590	0.010	Series has a unit root	Reject null -> stationary
KPSS (Level)	0.176	0.100	Series is level stationary	Fail to reject -> stationary
ADF and KPSS test opposing null hypotheses; joint agreement confirms stationarity without differencing.				

Table 2. ARIMA(0,0,2)(2,0,0) Specification [12]

Term	Estimate	Std. Error	z-value	p-value
ma1	0.5975	0.0598	9.992	< 0.001
ma2	0.1354	0.0622	2.177	0.029
sar1				
0.1970				
0.0567				
3.474				
< 0.001				
sar2	0.1868	0.0583	3.204	0.001
intercept	0.0021	0.0005	4.200	< 0.001
AIC = -2602.13 BIC = -2579.93 Log-likelihood = 1307.07 Inflation surprise series: mean = -6.64e-06, SD = 0.0031, range = [-0.0152, 0.0089]				

Table 3. Ljung-Box Test on ARIMA Residuals

Metric	Value
Ljung-Box Q*	28.61
Degrees of Freedom	20
p-value	0.096
Conclusion	Fail to reject -> no residual autocorrelation
Failure to reject the null indicates no remaining autocorrelation in residuals.	

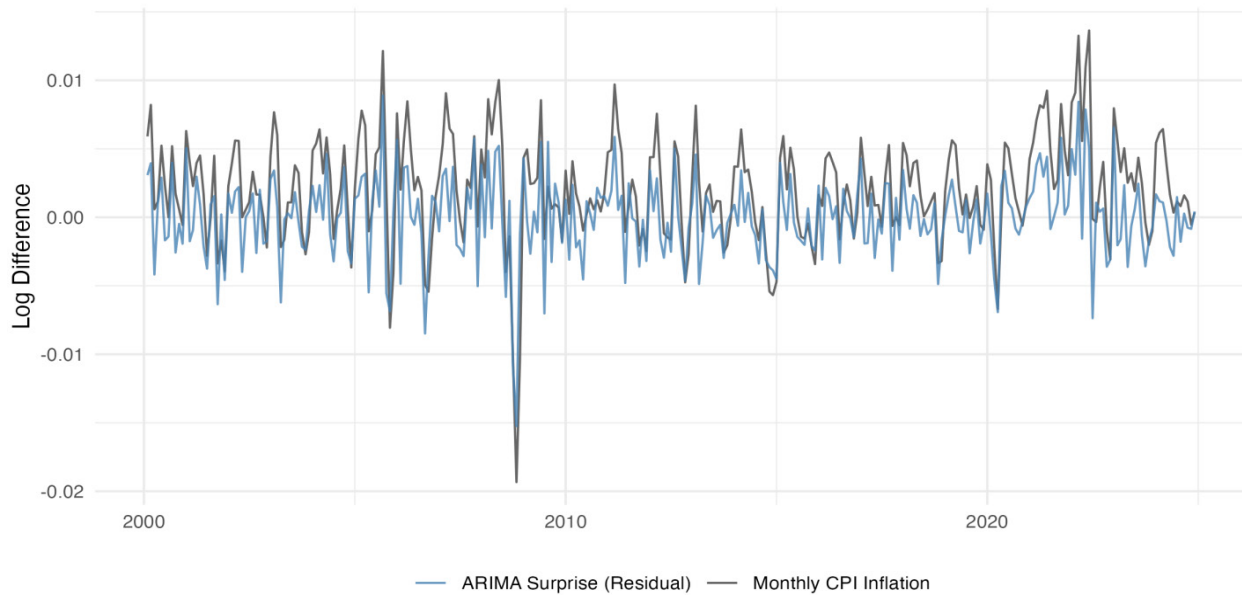


Fig. 1 Monthly CPI Inflation vs. Extracted Inflation Surprise

5.2 GARCH Findings: Inflation Uncertainty and Volatility Dynamics

Prior to estimating the GARCH model, the Engle ARCH LM test, which results in a rejection of the null of constant variance, is used to confirm the presence of time-varying volatility in the inflation surprise series, validating the use of a GARCH framework (Table 4).

Inflation volatility responds meaningfully to recent shocks and exhibits strong persistence (both ARCH and GARCH terms significant). $\alpha + \beta = 0.916$: high but still mean-re-

verting (Fig. 2). The Ljung-Box tests on standardized residuals and squared residuals confirm the model adequacy, indicating no remaining serial correlation or ARCH effects. The Sign Bias test is insignificant across all specifications, validating the use of the symmetric GARCH(1,1) specification over asymmetric alternatives, though the Nyblom stability test flags instability in the variance intercept (Table 5; Fig. 3). This is consistent with structural shifts in baseline inflation volatility across the three major crisis episodes in the sample.

Table 4. Engle ARCH-LM Test on ARIMA Residuals (12 lags)

Metric	Value
Chi-squared statistic	25.66
Degrees of Freedom	12
p-value	0.012
Rejection of the null confirms time-varying volatility, validating the GARCH specification.	

Table 5. GARCH(1,1) Model Results: Estimates, Diagnostics, and Stability

Item	Statistic	Std. Error / Critical Value	p-value
Parameter Estimates			
mu	-0.0001	0.0002	0.472
omega	0.0000	0.0000	0.579
alpha1 0.1406		0.0470	0.003
beta1	0.7750	0.0462	< 0.001
Residual Diagnostics			

Item	Statistic	Std. Error / Critical Value	p-value
Weighted Ljung-Box (standardized residuals)	0.0120		0.912
Weighted Ljung-Box (squared standardized residuals)	0.2490		0.618
Sign Bias (joint effect)	1.0870		0.780
Nyblom Stability			
Individual: mu	0.0360	5% crit = 0.47	
Individual: omega	4.9770	5% crit = 0.47	
Individual: alpha1	0.1380	5% crit = 0.47	
Individual: beta1	0.2730	5% crit = 0.47	
Joint	34.3320	5% crit = 1.24	
Persistence (alpha + beta) = 0.916. Weighted Ljung-Box statistics are rugarch's Lag test [1]. Sign Bias and Nyblom tests assess adequacy and parameter stability of the symmetric GARCH(1,1) specification.			

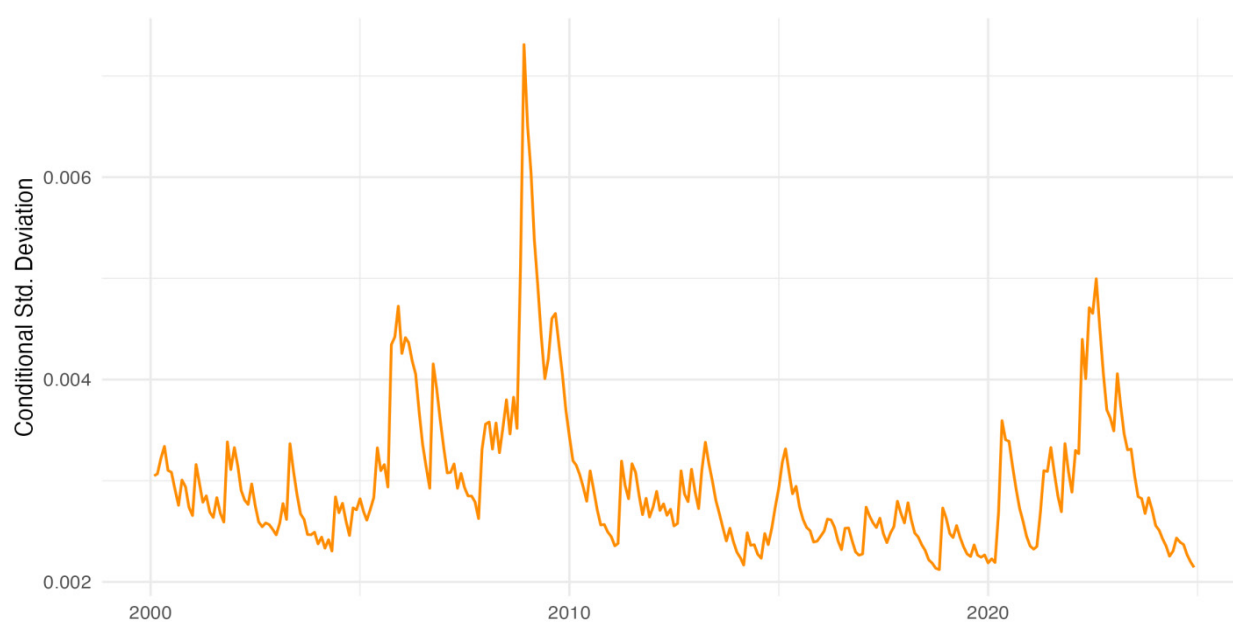


Fig. 2 GARCH(1,1) Conditional Volatility of Inflation Surprises

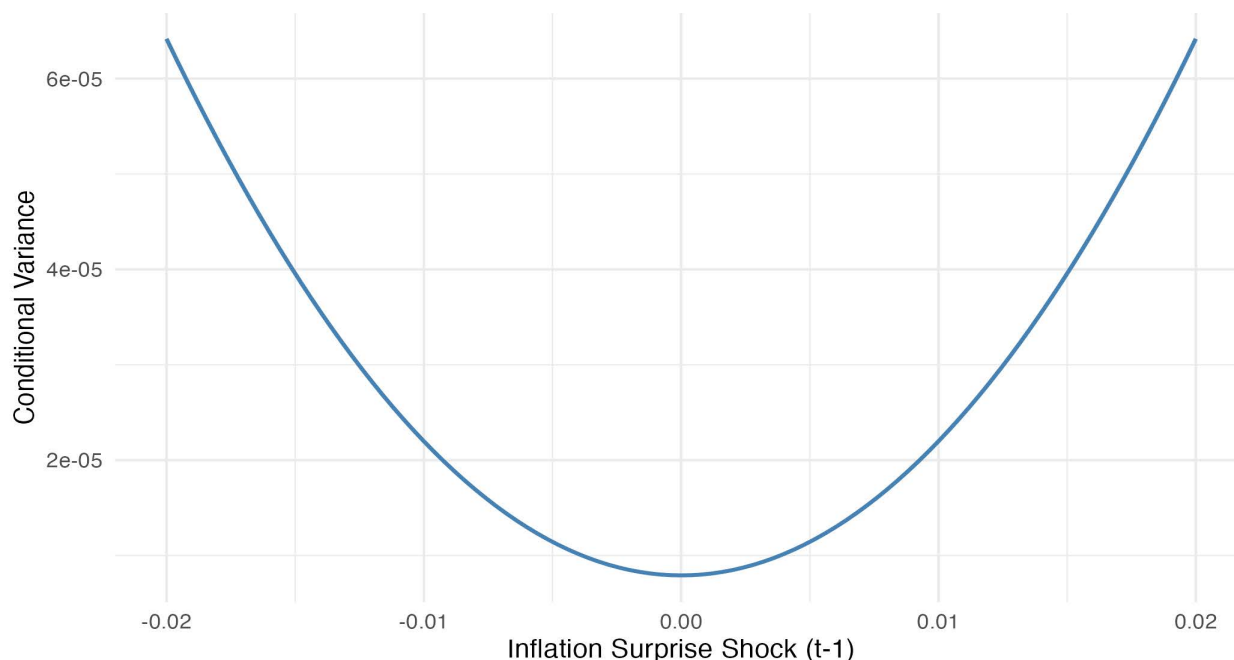


Fig. 3 News Impact Curve

5.3 Cross-Market Effects: Asset Class Responses to Inflation Shocks

The correlation between the inflation surprise series and conditional variance is negligible, confirming that the two regressors are sufficiently independent to enter the cross-market regressions separately, with each asset return series regressed on both the inflation surprise and conditional variance as distinct regressors (Table 6).

Commodity prices exhibit by far the strongest and most significant response to inflation surprises ($\beta = 2.981$, $p < 0.001$), with an R^2 of 0.565 — a remarkably high explanatory power for monthly financial data (Table 7). When inflation exceeds expectations, commodity prices surge, reflecting the mechanical relationship between commodity prices and the CPI. In addition to responding to inflation surprise, commodity prices also depend greatly on conditional variance, suggesting that sustained inflation uncertainty ultimately suppresses producer price growth by dampening producer activity.

Although treasury yields respond significantly and positively to inflation surprises, consistent with the fact that

unexpected inflation prompts investors to demand higher nominal yields to preserve real returns, conditional variance does not significantly affect yield changes, indicating that it is the inflation surprise itself, rather than broader uncertainty, that drives Treasury market adjustments (Table 8).

The U.S. dollar exhibits a marginally significant negative response to inflation surprises. This shows that unexpected inflation is associated with mild dollar weakness over the sample period (Table 9). This result, seemingly contrary to common belief, likely reflects episodes where high inflation coincided with broader dollar selloffs, such as 2002–2008 and 2020–2022, dominating the aggregate relationship.

Equity returns show no statistically significant response to either regressor at conventional levels, though conditional variance carries a negative coefficient, consistent with uncertainty-driven risk premium expansion compressing stock valuations (Table 10). Nonetheless, it is important to note the lack of statistical significance of these equity returns coefficients makes it difficult to draw conclusions with certainty.

Table 6. Correlation Between Inflation Surprise and GARCH Conditional Variance

Metric	Value
Pearson correlation (r)	-0.043
t-statistic	-0.74
p-value	0.460
Low, insignificant correlation supports entering both series as separate (non-interacted) regressors below.	

Table 7. Commodities Return Regression

Term	Estimate	Std. Error	t-value	p-value
Intercept	0.0046	0.0009	4.921	< 0.001
Inflation Surprise (ϵ)	2.9810	0.1547	19.266	< 0.001
Conditional Variance (h)	-244.1259	85.8678	-2.843	0.005

$R^2 = 0.565$ | Adj. $R^2 = 0.562$ | $N = 299$ | F-test p-value = < 0.001

Table 8. 10Y Treasury Return Regression

Term	Estimate	Std. Error	t-value	p-value
Intercept	-0.0014	0.0246	-0.055	0.956
Inflation Surprise (ϵ)	12.8192	4.0848	3.138	0.002
Conditional Variance (h)	-658.3875	2,266.9150	-0.290	0.772

$R^2 = 0.033$ | Adj. $R^2 = 0.026$ | $N = 299$ | F-test p-value = 0.007

Table 9. DXY Return Regression

Term	Estimate	Std. Error	t-value	p-value
Intercept	0.0010	0.0025	0.413	0.680
Inflation Surprise (ϵ)	-0.8119	0.4207	-1.930	0.055
Conditional Variance (h)	-101.2449	233.4585	-0.434	0.665

$R^2 = 0.013$ | Adj. $R^2 = 0.006$ | $N = 299$ | F-test p-value = 0.148

Table 10. S&P 500 Return Regression

Term	Estimate	Std. Error	t-value	p-value
Intercept	0.0128	0.0051	2.523	0.012
Inflation Surprise (ϵ)	0.8504	0.8418	1.010	0.313
Conditional Variance (h)	-850.6438	467.1604	-1.821	0.070

$R^2 = 0.015$ | Adj. $R^2 = 0.008$ | $N = 299$ | F-test p-value = 0.107

5.4 Stress Test Results: Portfolio Performance Under Inflationary Stress

To construct a simulated portfolio, stress episodes had to first be identified. Defined as months where the GARCH conditional variance exceeded 1.5 standard deviations above its sample mean (threshold = 1.759×10^{-5}), 22 such stress episodes are marked (Table 11). These episodes clustered across three distinct periods of macroeconomic hardship: the energy price surge of October 2005–March 2006, the Global Financial Crisis of November 2008–October 2009, and the post-COVID inflation surge of April–September 2022. The three stress periods correspond to macroeconomic disruptions, and inflation uncertainty exhibits sharp spikes rather than gradual drift (Fig. 4).

An equal-weighted portfolio comprising the S&P 500,

10-year Treasury, DXY, and PPI All Commodities index was constructed to assess aggregate performance across regimes. Remarkably, the portfolio generated a mean monthly return of 0.851%, greater than the -0.078% return during normal periods. However, this return differential comes at substantially higher risk: portfolio volatility during stress periods was 9.02%, versus 5.53% during normal periods, representing a 63% increase in risk (Table 12 this paragraph).

The 10-year Treasury dominates stress period performance with a mean monthly return of 4.14% (Fig. 5), reflecting a strong flight-to-safety dynamic as investors prioritize capital preservation over inflation hedging (Table 12). Surprisingly, commodities prices declined during stress episodes, despite their positive relationship with inflation surprises documented in Table 10. This inver-

sion suggests that demand destruction and recession fears outweigh the inflation hedge property under sustained uncertainty. One interesting result here: the DXY exhibited marginal positive performance over the stress episodes

but had a marginally significant negative relationship with inflation surprise over the full sample period. Equities declined modestly, compatible with the idea of growth fears overwhelming any inflation premium.

Table 11. Identified Inflation-Uncertainty Stress Episodes

Episode	Start	End	Months	Mean Cond. Variance
Episode 1	2005-10-01	2006-03-01	6	0.000020
Episode 2	2008-11-01	2009-05-01	7	0.000033
Episode 3	2009-07-01	2009-10-01	4	0.000020
Episode 4 2022-04-01 2022-04-01 1 0.000019				
Episode 5	2022-06-01	2022-09-01	4	0.000022
Stress threshold = mean + 1.5 SD of conditional variance = 1.759e-05 Total stress months = 22				

Table 12. Stress vs. Normal Period Performance: Portfolio and Asset Level

Series	Stress Return	Normal Return	Stress Volatility	Normal Volatility
Equal-Weighted Portfolio	0.851%	-0.078%	9.018%	5.531%
S&P 500	-0.520%	0.561%	6.543%	4.246%
10-Year Treasury	4.136%	-1.148%	35.340%	20.384%
DXY	0.154%	-0.001%	2.918%	2.163%
Commodities	-0.367%	0.275%	1.888%	1.155%

Portfolio volatility rises ~63% in stress periods; the Treasury's flight-to-safety swing and the commodity paradox drive the asset-level divergence.

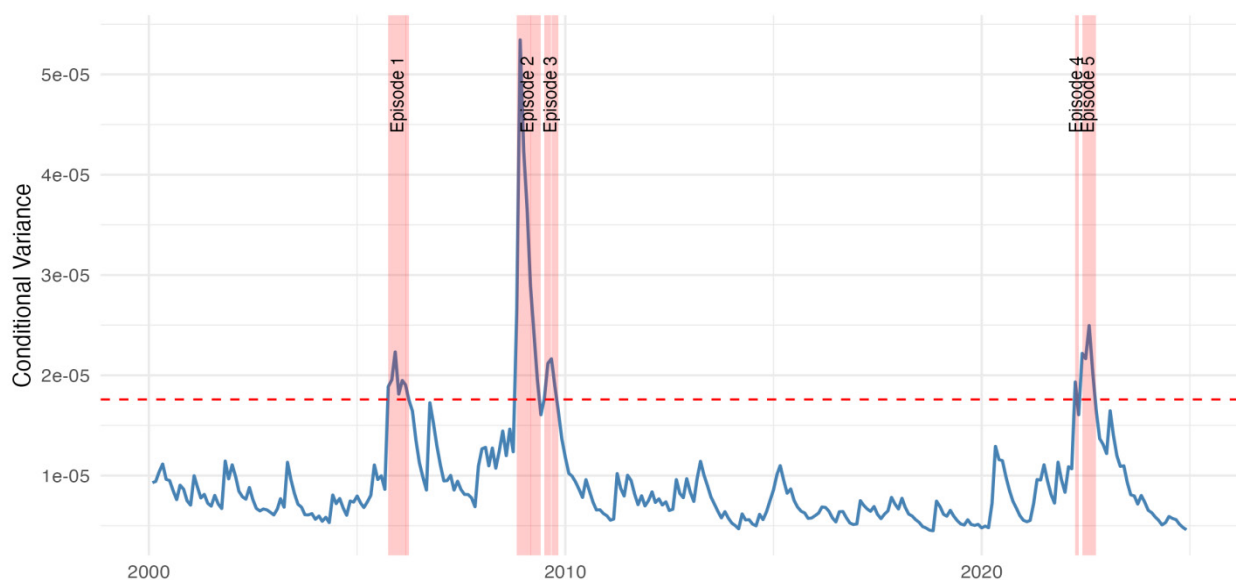


Fig. 4 Inflation Uncertainty (GARCH Conditional Variance)

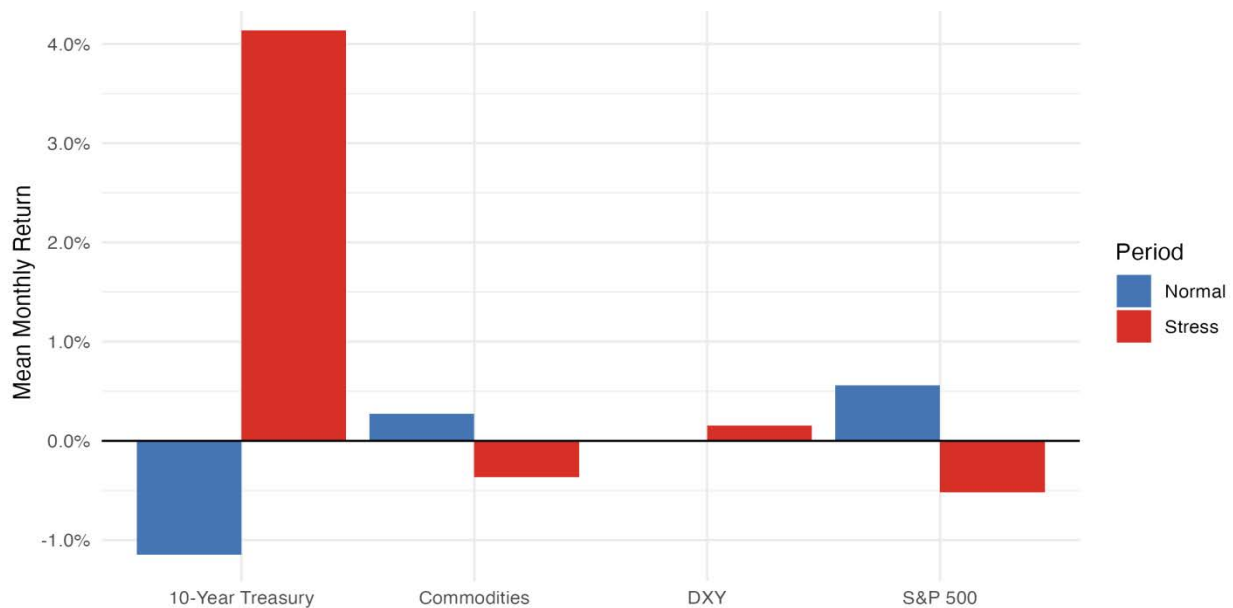


Fig. 5 Mean Asset Returns: Stress vs. Normal Periods

6. Conclusion

This paper used an ARIMA-GARCH method to examine the impact of inflation surprise and uncertainty on cross-asset returns across U.S. equities, Treasury bonds, the dollar, and commodities from 2000 to 2024. Four findings occurred: ARIMA isolated unanticipated inflation deviations; GARCH(1,1) confirmed uncertainty is persistent and clusters around three crisis episodes; cross-market regressions showed commodities responding most strongly to surprises and Treasury yields adjusting per the Fisher effect, while equities showed no significant sensitivity; and stress testing revealed a commodity paradox, with commodity prices declining during acute uncertainty while Treasuries became the safe asset.

The findings of this paper are the most significant to portfolio managers. The results support a macroeconomic-dependent allocation method: during periods of moderate inflation surprise, overweighting commodity exposure and maintaining reduced fixed income exposure is empirically justified. Under acute inflation uncertainty, however, a more defensive reallocation toward Treasuries is warranted, since commodity price exposures can no longer adequately serve as hedges. Risk officers and policymakers can also find this paper's results helpful as the GARCH conditional variance can be used to deduce a reliable real-time signal for identifying stress regime transitions, and the persistence of inflation uncertainty ($\alpha + \beta = 0.916$) and its episodic nature can be seen as evidence for the importance of clear and credible communication.

The biggest limitation of the analysis was the use of US-centric data, as it limits the generalizability of findings to

other economies with different monetary policy frameworks or inflation dynamics. In addition, monthly data frequency may have missed higher-frequency dynamics as intra-month inflation news releases and asset price adjustments may have carried information not captured at the monthly level. It is also worth mentioning that the current cross-market regressions assumed linear relationships between inflation surprises and asset returns, potentially missing nonlinear or threshold effects, though the implication of these effects remains unclear.

The most direct extension of the current framework is the use of daily data, which would allow clearer resolution of inflation surprise transmission across asset classes and potentially reveal lead-lag relationships obscured at the monthly frequency. Rerunning the analysis with BCOM can provide insights into whether price-level findings translate to commodity returns. A multivariate DCC-GARCH specification, for example, would capture time-varying cross-asset correlations under inflationary stress, providing richer insight into contagion dynamics. That specification is incompatible on the datasets in this paper, but altering the scope of study with different data can yield fruitful results. Since the previous section recognizes US-centric data as a limitation, extending the analysis to emerging markets in Asia to see if the flight-to-safety and commodity paradox findings hold beyond the U.S. context would also prove insightful.

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